ROBO-ADVISORS: EXPLORING AND LEVERAGING THE COMPETITON

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Bridging the Gap Between Theory and Practice

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ABSTRACT

There are lot of talks about robo-advisors taking the jobs of human financial advisors. Amid the excitement or anxiety about robots doing better than humans in many aspects, there is little discussion on the potential limitations of machines in taking over certain aspects of the financial planning process. What are the technologies behind robo-advisory systems, what are the pitfalls, and will they really replace human advisors? In this paper, I review recent literature on robo-advice and conclude that human advisors adopting robo-advisors into their practices will enhance their practices even further and deliver better outcomes than either standalone robo-advisors or human advisors.

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ROBO-ADVISORS

EXPLORING AND LEVERAGING THE COMPETITION

1. INTRODUCTION

Among the interesting developments in the asset management industry is the emergence of robo-advisors. Even with this emerging trend, the classical Markowitz mean-variance optimisation remains the the most popular investment technique. Possibly, robo-advice is currently the most significant disruptive trend in asset management. Although it has become a popular buzzword, there is little known about the core portfolio optimisation strategies of these systems. Beketov, Lehmann and Wittke (2018) analysed 219 robo-advice platforms worldwide and found that MPT is the most popular framework among robo-advice systems followed by Sample Portfolios and Constant Portfolio Weights (Table 1). Currently, the trend is to build upon the existing frameworks instead of developing and implementing entirely new frameworks.

The term robo-advice encompasses a wide array of digital automatic and semi-automatic investment services and platforms. Sironi (2019: 22) argues that "Automated Investment Solutions" (AIS) would be a more appropriate name for robo-advisors as they are neither robots nor advisors . However, "we are aware that AIS would not be a headline stealer, because it does not convey the same emotional emphasis as "robotics". So Robo-Advisors it is!". There are currently four generations of robo-advice systems (Deloitte 2016a; Deloitte 2016b). The first and second-generation robo-advice systems comprise online questionnaires and proposals, and provide a mix of advice and online access to traditional ''manual'' services in wealth management. The third and fourth generations on the other hand, employ algorithms and quantitative methods to create and rebalance portfolios. In essence, these generations of robo-advisors provide fully automated services in wealth management and only differ in terms of the extent of automation and advances in methodologies (Deloitte 2016a; Deloitte 2016b).

2. ASSET ALLOCATION STRATEGIES OF ROBO-ADVISORS

Beketov, Lehmann and Wittke (2018) studied the asset allocation strategies of selected robo-advice systems and report that some systems do not provide any information on their asset allocation strategy; other systems have no asset allocation strategy at all - these were the first and second generation robo-advice systems that do not have any portfolio optimisation strategy in place. For robo-advice platforms which had optimisation strategies in place, shows the occurrence of the strategies used. This includes the names of all of the methods found on the companies' websites. The size of the names is proportional to the frequency of occurrence.

Table 1: Occurrence of Different Methodologies in Robo-Advisory

Methodological framework	Occurrence (%)	Methodological framework	Occurrence (%)
Modern Portfolio Theory	39.7	Risk Parity	1.4
Sample Portfolios	27.4	Full-Scale Optimisation	1.4
Constant Portfolio Weights	13.7	Constant Proportion Portfolio Insurance	1.4
Factor Investing	2.7	Mean Reversion Trading	1.4
Liability-Driven Investing	2.7	Other	8.2

Beketov, Lehmann and Wittke (2018: 366)

Figure 1: Method Occurrence

Beketov, Lehmann and Wittke (2018: 366)

An analysis of the relationship between method occurrence and assets under management revealed that MPT has the highest asset under management. Relatively advanced methods such as Black–Litterman model (Black and Litterman 1991; Black and Litterman 1991) and Full-Scale Optimisation (Adler and Kritzman 2007; Cremers, Kritzman and Page 2005) attract high overall AuM although they had relatively low occurrences. The relatively simple and generally defined methods such as Constant Portfolio Weights and Sample Portfolios had more occurrences but attracted relatively lower AuM.

3. TECHNOLOGIES BEHIND ROBO-ADVISORY SYSTEMS

Chia (2019) examined the application of artificial intelligence (AI) and deep learning, specifically, in the design of robo-advisors and reported that robo-advisors have the potential to be perfectly honest fiduciaries who act in the best interest of clients, devoid of greed or any conflict of interest unlike their human advisors. However, the application of AI or deep learning technology to design robo-advisors is not without risk. One of the major concerns with deep learning is that it is a "black box" with opaque decision-making process and not open to scrutiny even by its developers. This creates a huge challenge for regulators as they will not be able to examine the underlying rules and rationale of such robo-advisors to determine their safety for public use. Smith (2019: 1) for example argues that computer "intelligence" is very different from human intelligence. Trading algorithms, for example, understand the world in any meaningful sense, and are consequently risky. They are very efficient in discovering statistical patterns, but completely useless in judging whether the patterns discovered are coincidental or consequential.

In one of the Avengers movies, Tony Stark (Iron Man) creates Ultron, an AI defense system to protect the earth. Ultron literally interprets the task and concludes that the best way to protect the earth is to destroy all humans. In many ways, Ultron, just like any typical algorithm, does exactly what it is told to do and disregards every other consideration. Algorithms are important tools for planning; however, they can easily lead decision-makers to wrong conclusions. All algorithms have two main characteristics: They are literal and will do exactly what they are asked to do. Secondly, they are black-boxes, and do not explain why they reach certain conclusions (Luca, Kleinberg and Mullainathan, 2016). It is therefore important to understand the technology behind a particular robo-advisory system because different technologies perform different tasks and each technology has its strengths and limitations. Robotic process automation and rule-based expert systems, for example, have transparent processes and procedures of operations incapable of learning and improving. Deep learning, on the other hand can learn from large volumes of labelled data, but it is almost impossible to comprehend how it develops its models. In heavily regulated industries such as financial services, where regulators require explanations on why decisions are made in a certain way, this black-box issue can be problematic.

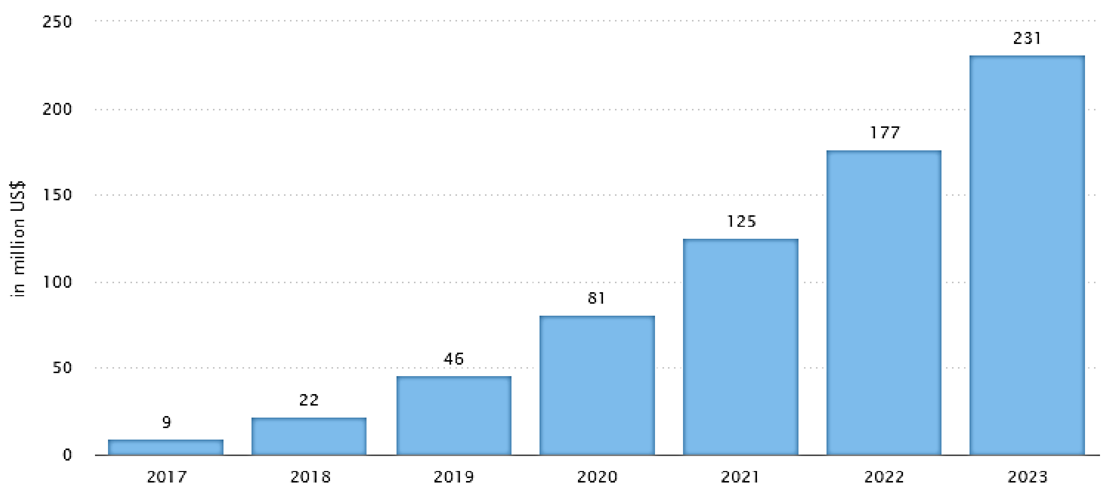
Table 2: Summary of the Main Building Blocks of Robo Advisors

Asset universe selection	Investor profile identification	Asset allocation/portfolio optimisation	Monitoring and rebalancing	Performance review and reporting
All platforms use ETFs with a few exceptions including Mutual/Actively Managed Funds, Sustainable Funds, ETCs, and Index Funds. Different selection criteria include total costs, expense ratio, liquidity, replication method, and correlation among the ETFs	Online questionnaires focused on the identification of risk tolerance of clients, investment objectives and time horizon. Usually, the questions are compiled to elicit the objective risk tolerance through information on previous investment experience, income, savings, age and investment goals.	Most of the platforms apply MPT, supplemented and modified by other methods (e.g., Black–Litterman, VaR and CVaR optimisation). Noteworthy exceptions include Constant Proportion Portfolio Insurance, Full-Scale Optimisation and Risk Parity. Only a few platforms apply constant portfolio weights.	Most platforms implement event/ threshold-based rebalancing based on the daily rebalancing check. The triggers are defined as portfolio structure (i.e., weights), returns (drift), and VaR. Some platforms implement calendar-driven rebalancing. Others also use optimised dividend and cash-flow (re)investment for the rebalancing	50 per cent of the platforms offer monitoring and control options through the website only. The other 50 per cent also provide smartphone apps. Some platforms send the monthly and quarterly statements automatically via e-mail

4. THE ROBO-ADVISORY LANDSCAPE IN SOUTH AFRICA

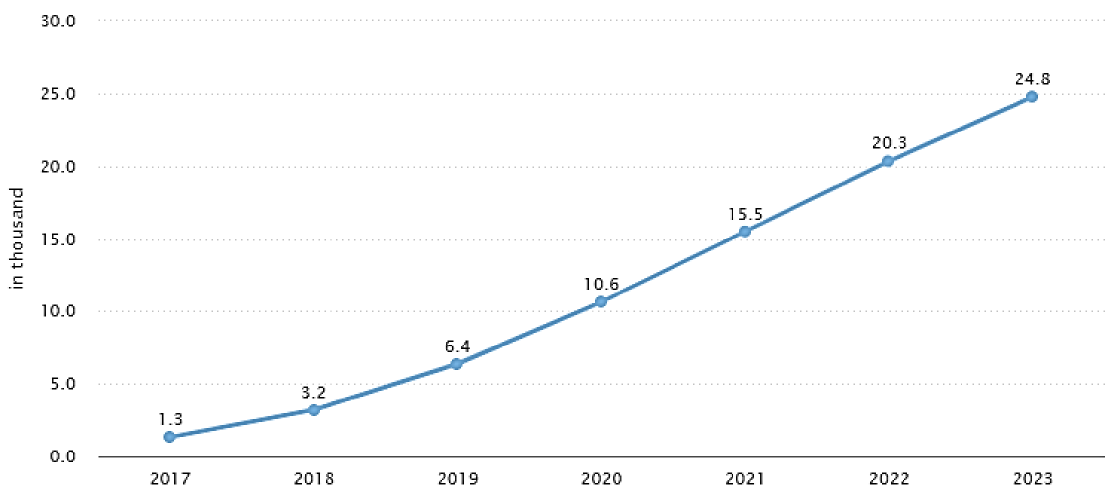
In South Africa, the robo-advisory space is relatively small, with only a small number of banks, fund managers and financial advisors currently employing robo-advisors in their practice. By 2023, robo-advisors will manage $231 million in South African assets, growing from up from only $9 million in 2017 according to data from Statista. Figure 3 shows the assets under management (AuM) and projected AuM of SA robo-advisory platforms. Figure 4 shows the number and projected number of robo-advice users in SA and Figure 5 shows the AuM per user and projected AuM per user.

Figure 2: SA Robo-Advisory Assets Under Management



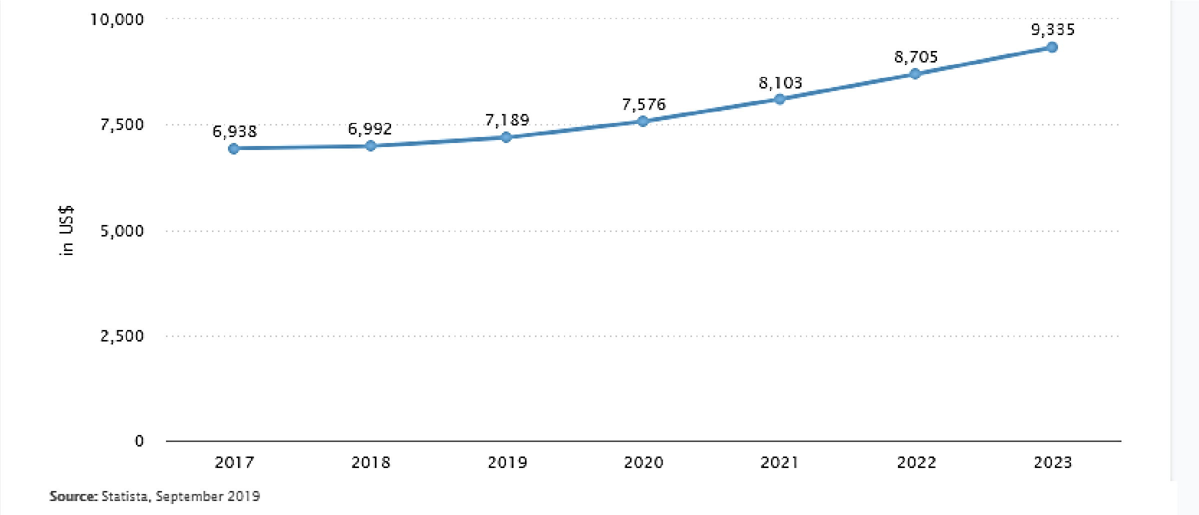
Source: Statista, September 2019

Figure 3: Number of Robo-Advice Users in SA



Source: Statista, September 2019

Figure 4: SA Robo-Advisory Assets Under Management Per User



Robo-advisory platforms that have been set up in South Africa include Nedgroup Investment Advisor's Eva, Sygnia RoboAdvisor, Sanlam Smart Invest, OUTvest and Bizbank backed by Anchor Capital. Sanlam's Smart Invest starts with asking what you are investing for and gives five options to choose from: Education, My Future Self, Just Investing, Dream Home and Something Special. Should you select Just Investing, for example, you are given the options to continue with your goal or launch a calculator. Among other steps, Smart Invest gives you the option to calculate your risk profile based 18 questions. Once you accept this risk profile suggested, you are provided with investment options to choose from to meet your goal. Nedgroup Investment's Eva as well as OUTvest take an easy-to-answer approach and can generate recommendations in under 10 minutes.

Currently, there is no specific regulations in South Africa on robo-advisors, however, the Financial Sector Conduct Authority (FSCA) has issued a definition of robo-advice in the latest draft of the FAIS Fit and Proper regulations. It defines robo-advice as "the furnishing of advice through an electronic medium that uses algorithms and technology without the direct involvement of a natural person". There are currently no rules prevent robo-advisors from carrying out the entire financial advice process, from risk profiling to selecting suitable investments, to reviewing the investments over time. The regulator however requires each platform provider to appoint at least one key individual who meets the regulatory competency requirements and understands the algorithms, assumptions and risks incorporated in the platform.

5. ROBO-ADVISORS AND FINANCIAL PLANNING

Tertilt and Scholz (2018) investigated how robo-advisors evaluate the risk preferences of private investors by studying seven German robo-advisors and six market-leading robo-advisors from the United Kingdom and the United States (three from each country). The study found that during the planning phase of the portfolio management process, robo-advisors tend to use fewer questions than human advisors and sometimes ask questions that have no impact on the categorisation of risk. Currently, there seem to be no benefit or only a marginal benefit from risk assessment or big-data analysis implemented by robo-advisors.

Furthermore, there appears to be little support in assisting clients to reflect on their risk appetite and goal-specific risk budget. Portfolio recommendations of the robo-advisors were also rather conservative (Tertilt and Scholz, 2018). For clients, robo-advisors can be straightforward and timesaving, however, robo-advisors might not be able to know clients as well as traditional advisors do through tailored questions, multiple interactions and closer relationships. "One-size-fit-all" questionnaires may be too simple and narrow to give a complete overview of the needs and financial situation of the client. Furthermore, these questionnaires assume that individuals with a similar risk profile will give the same answers to the same subjective questions; this may not be necessarily true (Deutsche Bank 2017).

Robo-advisors also lack other important aspects of a client-advisor relationship, such as counselling in times of market downturns, dealing with possible changes in the client's life or assisting clients to define their financial goals (Accenture 2015). The process of defining financial goals go beyond simply asking the client about her goals. A client may give a response which may sound reasonable, however, studies show that many of these on-the-spot responses tend to be top-of-mind priorities that might not reflect goals that are truly important to the client. These thinking blind spots are as a result of behavioural biases we all share (Benartzi and Lewin, 2015), and these biases can wreak havoc on even the best-developed financial plans. It can also prevent clients from reporting their true goals and lead to financial plans that do not accurately reflect their preferences and motivations. Without proper guidance, people usually fail to identify as many as half of the goals that they later recognise to be crucial to their plans (Bond, Carlson and Keeney, 2008). In these situations, such knee-jerk goals may not be a full reflection of the financial life that is truly important to the person.

Sin, Murphy and Lamas (2018) investigated a range of issues in goal setting and prioritisation, and one study, they attempted to mimic the typical goal-identification process by asking the participants to list and rank their top three financial goals. They then added the self-reported goals of the participants, in a random order, to a master list (Table 3) of common financial goals to create a combined list. After looking at the combined list, the participants were asked to rank all their financial goals in order of importance.

Table 3: Master List of Financial Goals

1	To be better off than my peers
2	To pay for personal self-improvement (e.g., go back to school, learn a skill)
3	To experience the excitement of investing
4	To start a new business
5	To buy a house
6	To help pay for my kids' college education
7	To stop working and do something I love
8	To go on a dream vacation
9	To relocate in retirement
10	To care for my aging parents
11	To give to charity or other causes I care about
12	To feel secure about my finances in retirement
13	To feel secure about my finances now
14	To leave an inheritance to my loved ones
15	To retire early
16	To pay for future medical expenses
17	To not be a financial burden to my family as I grow older

Sin, Murphy and Lamas (2018)

If the master list has no influence on identifying goals, then participants would select the same top goals they self-reported compared to the goals they identified after seeing the master list. Interestingly, this was not the case. On average, 26 per cent of participants changed their top goal after they saw the master list. The master list even had more influence on multiple-goal scenarios: About 73 per cent of participants substituted at least one of their top three goals with goals from the master list. This means only about 26 per cent of participants retained all their top three initial financial goals. A human advisor may be able to guide a client in setting financial goals but this may not be the case with a robo-advisor.

Furthermore, robo-advisors might not ask about other investments of a client (for example, pension funds and real estate), insurances purchased, potential liabilities, future expenses or spouse's financial condition among other information (FINRA 2016). If robo-advisors act on partial information, the recommendation they provide might not be the most suitable for the client. There is also the risk of client disengagement when clients use robo-advisors. Since the entire advisory process is automated, clients may not make efforts to understand how the service works, or even regularly monitor their investments. This issue is especially relevant for individuals with relatively lower wealth and do not have any experience with investment products (OECD 2017).

There are also legal implications for investor protection with regard to robo-advisors. Upon examination of the complex state of financial innovation and established investor protection regimes in the United States, Strzelczyk (2018) argued that the laws do not adequately deal with the question of whether a robo-advisor platform which serves as registered investment adviser meets the standard fiduciary requirements. Strzelczyk analysed the current regulation from the Financial Industry Regulatory Authority, the Department of Labor and the Securities and Exchange Commission and concluded that robo-advisors cannot serve as fiduciaries. The main reason being that these platforms do not offer the kind of personalised portfolio analysis provided by traditional fiduciary agents.

In 2017, the Association of National Advertisers (2017) selected "AI" as the Marketing Word of the Year. To a certain degree, the allure of robo-advisors can be attributed to the success of computer programs beating humans in games like chess, checkers and Go. However, in these games, the goals and tasks are narrow and clearly defined. Although computer programs can quickly make calculations, possess infallible memory and flawlessly follow rules, they do not possess anything resembling the general intelligence required to deal with ill-defined state of affairs, unfamiliar situations, vague rules and ambiguous or even contradictory goals (Smith, 2019). Furthermore, robo-advisors are relatively new, and their business models have not been tested in the long term and under financial stress. Therefore, it is still unclear to what extent clients will be protected in situations where a robo-advisor company fails. Some jurisdictions have implemented mechanisms to protect clients; robo-advisors in the United States, for example, are required to be members of the Securities Investor Protection Corporation (SIPC), which provides insurance for up to $ 500 000 per client in the event of bankruptcy of a member firm (Abraham, Schmukler and Tessada, 2019).

6. LEVERAGING THE COMPETITION

In this age of AI, humans are still needed to carry out three crucial roles: They must train machines to execute certain tasks; explain the outcomes of those tasks, particularly when the outcomes are controversial or counterintuitive; and maintain the responsible use of machines (for example, by preventing robots from harming humans). As recommendations by AIs are increasingly reached through opaque (black box) processes, they require human with expertise in the field to explain their behaviour to nonexpert users. These "explainers" are particularly important in evidence-based and heavily regulated industries such as medicine, law and financial services. Explainers are becoming an integral part of regulated industries especially in consumer-facing industries where the recommendations of a machine could be challenged as illegal, unfair or simply wrong. The General Data Protection Regulation (GDPR), the European Union's (EU) law on data protection and privacy, for example, gives consumers the right to explanations for any algorithm-based decision, such as the rate offer on a mortgage or credit card (Wilson and Daugherty, 2018).

The jury is still out as to whether the services and benefits provided by robo-advisors are equal to or better than those provided by traditional financial advisors. In addition to significantly lower fees charged compared to traditional advisors, adopting robo-advice reduces well-known behavioural biases for all investors (D'Acunto, Prabhala and Rossi 2019). Undiversified investors also benefit more from robo-advice; the technology makes implementation of advice simple for the less savvy investors. Robo-advice therefore can be an effective approach to help investors diversify their portfolios, compared with other types of advice (Bhattacharya, Hackethal, Kaesler, Loos and Meyer, 2012; Linnainmaa, Melzer, and Previtero 2017).

An increasing body of research suggests that the future of the financial planning industry, however, lies in a hybrid of traditional and robo-advisors. A combination of the two will lead to a highly-performing and cost-efficient hybrid advisory system. A *cyborg advisor*! Traditional/human advisors can leverage robo-advisors to deliver additional value to clients beyond what a stand-alone robo-advisor or traditional advisor can deliver. Since the robo-advisor is optimised algorithmically to select low cost securities (usually index funds and ETFs) to create highly diversified and optimised portfolios to meet clients' risk tolerance, traditional financial advisors can benefit immensely by leveraging robo-advisors. The hybrid advisor can take the robo-advisor further by *anxiety-adjusting* (customising) these optimised investment sets to produce *best practical* and *palatable* portfolios which clients can comfortably stick with to help reach their goals. Adapting robo-advisors will help the human advisor save time and thus commit more time towards focusing on her strong-suit to establish a stronger emotional connection, build trust and enhance the client-advisor relationship. Robo-advisors can be used in the implementation and feedback phase of the portfolio management process to create, continually monitor and review financial plans. One advantage of the robo-advisor is that it is not prone to behavioural biases and it can continually rebalance clients' portfolios to help them reach their goals irrespective of market conditions.

To maintain a strategic asset allocation, the robo-advisors can notice straight away when the weights in a portfolio begin to drift and rebalance accordingly. Although human intervention is sometimes required, employing the robo-advisor to monitor and rebalance portfolios will help the human financial advisor save time, avoid costly mistakes and serve clients needs more efficiently. A combination of face-to-face client meetings with digital interaction can enable to advisor cater to the specific needs of each client on a more consistent basis. Furthermore, incorporating robo-advisor technology can enable the advisor capture new demographics such as Generation Y, who tend to have low investment balances and prefer 24/7 technological access to their investments.

Humans and machines can augment each other's strengths and compensate for weaknesses which can lead to better outcomes than humans or robots working alone. Vanguard's Personal Advisor Services (PAS), for example, combines automated investment advice with guidance from human advisors. This system uses cognitive technology[1] to perform many of the traditional tasks in investment advisory which includes developing customised portfolios, tax-efficient investment selection, portfolio rebalancing and tax loss harvesting. According to Davenport and Ronanki (2018), in some cognitive projects, 80 per cent of decisions will be made by robots and 20 per cent will be made by humans; others will have the opposite ratio. Artificial intelligence is transforming business processes and have the most significant impact when it augments humans instead of replacing them (Luca et al., 2016). With the PAS, the human advisors serve as "investment coaches" and serve as "emotional circuit breakers" to help investors stick to their investment plans. They also customise implementation plans, provide advice on estate-planning, monitor spending to encourage accountability, encourage healthy financial behaviours and answer questions from investors. Behavioural finance is increasingly becoming very crucial for human advisors and are encouraged to enhance their knowledge in the field to effectively perform their roles.

[1] Cognitive technology is a field of computer science that mimics functions of the human brain through various means, including natural language processing, data mining and pattern recognition.

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